Using Multiple Frequency Bins for Stabilization of FD-ICA Algorithms

Leandro E. Di Persia[a,*], Diego H. Milone[a]

[a] *Research Institute for Signals, Systems and Computational Intelligence, Faculty of Engineering and Water Sciences, National University of Litoral, and National Council for Science and Technology, Argentina*

Abstract

In the frequency domain independent component analysis approaches for audio sources separation, the convolutive mixing problem is replaced by the solution of several instantaneous mixing problems, one for each frequency bin of the short time Fourier transform. This methodology yields good results but requires the solution of the permutation ambiguity. Moreover, the performance of the separation algorithms for each bin is not guaranteed to be equivalent, thus some bins can have worse results than others. In this paper a technique based on data from multiple bins is proposed to address these issues. The use of multiple bin information produces a coupling of the separation, resulting in more stable separation matrices and reducing the occurrence of permutations, but increasing in computational cost. This can be mitigated by a sub sampling of the multiple bins information. The results show that both approaches are beneficial for the frequency domain ICA approach, producing better separation in terms of objective quality measures.

*Corresponding Author. Tel. +54 342 4575233 ext. 192

Email addresses: `ldipersia@sinc.unl.edu.ar` (Leandro E. Di Persia), `dmilone@sinc.unl.edu.ar` (Diego H. Milone)

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1. Introduction

The Audio Source Separation problem is very important for man-machine interfaces, domotics, robotics and many applications of communications [1]. One of the most successful approaches for this problem is the frequency domain independent component analysis (FD-ICA)[2, 3]. The time-domain mixture of sources in a real environment can be expressed as

$$\mathbf{x}(t) = H(t) * \mathbf{s}(t), \tag{1}$$

where $\mathbf{x}(t) = [x_1(t), x_2(t), \ldots, x_N(t)]^T$ is the vector of N measured signals or mixtures, $H(t)$ is a FIR matrix with impulse responses of the room from each source location to each microphone location, $\mathbf{s}(t) = [s_1(t), s_2(t), \ldots, s_M(t)]^T$ is the vector of M sources, and the symbol $*$ stands for convolution. This operation is similar to a matrix-vector multiplication, replacing scalar multiplication by filtering using a convolution. A usual assumption is that the number of mixtures N equals the number of sources M, a case known as determined mixture, that will be considered in this paper.

Using the short time fourier transform (STFT) (1) can be written as

$$X(\omega_k, \tau) = H(\omega_k)S(\omega_k, \tau), \tag{2}$$

where $X(\omega_k, \tau)$ is the vector of mixtures in the frequency domain, for frequency ω_k of bin k and time τ; the same for $S(\omega_k, \tau)$ but for the source signals, and $H(\omega)$ is a standard scalar matrix with the values of the filters for each frequency ω_k [3]. It must be noted that a stationary mixture was assumed in the previous equation, and thus H is not a function of the time index τ. This equation means that in the frequency domain, the convolutive mixture problem has been replaced by many instantaneous mixture problems, one for each frequency bin. This allows the problem to be solved efficiently by using any instantaneous ICA algorithm applied to each frequency bin, that is, to find a matrix $W(\omega_k)$ such that the estimated sources $Y(\omega_k, \tau) = W(\omega_k)X(\omega_k, \tau)$ result as statistically independent as possible.

One of the main disadvantages of the FD-ICA approach is that the solution of the ICA subproblems in each frequency bin will produce an arbitrary permutation and scaling of the sources. These ambiguities should be solved before applying the inverse STFT to return to the time domain. The amplitude ambiguity is usually solved by the Minimal Distortion Principle [4]. For the permutation ambiguity, there have been several approaches with different degrees of success, using for example the correlation among envelopes [5] or power ratios [2], the generalized coherence function [6], the use of information theoretic distance measures [7], or the pseudoanechoic model for blind source separation [8]. In the last case, the problem was simplified in such a way that it required the robust estimation of the separation matrix for only one frequency bin, which then will serve to estimate the parameters for defining the separation matrices for all bins.

One important problem of the FD-ICA approach is that, as each of the ICA subproblems is independently solved, the quality of the solution found for each of them will vary from bin to bin, and the problem will be worst for short signal duration [3]. This will produce a degradation of the separation, and also it can increase the difficulty in the disambiguation of the permutations. In [9] the separation quality for each bin is evaluated using the directivity patterns, and is shown that the direction of sources detected by the ICA method can vary a lot from bin to bin, due to poor results in the separation of individual bins.

To improve these issues we present an approach based on multiple frequency bin information as input data to each ICA subproblem. The use of multiple bins can be applied to the general FD-ICA framework, where an ICA subproblem needs to be solved for each frequency bin. The main hypothesis is that the addition of lateral bins can produce a more robust estimation of the separation matrices for all bins. That is, the main idea of this work is to provide robustness to the estimation of each separation matrix through the coupling of information of different bins. This would have an impact on both, the quality of separation for each individual bin and the production of less permutations, simplifying the postprocessing needed to obtain proper alignment of the separated components.

In Section 2 the general methodology to include multiple bin information is introduced. The algorithm is presented, and two variants of it are proposed. Section 3 presents the experimental framework and the comparative results. Finally, Section 4 presents the conclusions.

2. Methods

2.1. Standard FD-ICA

A recent review of the FD-ICA, with special emphasis to multichannel blind source separation, was given in [10]. A general framework for FD-ICA is presented in the flow chart diagram of Fig. 1. The first step is a transformation to the time-frequency domain by using a STFT with given window and step sizes. The next step is the estimation of the separation matrix for each frequency bin. As shown in the flow chart, this is performed by a sequence of three operations. First, the separation matrix obtained in the previous bin is used as initial value for the present bin as in [11]. This is done because the separation matrices should change slowly with the frequency, and thus using the previous estimated one is better than using a random matrix and provides a faster convergence. In the second operation, the data to be used to learn the separation for each bin should be selected. For standard FD-ICA this is simply all the data for the given frequency bin (this step is what will be modified by our proposed algorithms). In a third operation, the separation is done by the methodology proposed in [2]. The initial estimation is refined by using the complex FastICA method [12]. This method is very fast but the estimated separation matrix is not the best possible. Thus, it is further refined by using the Scaled Natural Gradient (SNG) ICA method [13]. The SNG ICA method is certainly efficient and the literature is rich in adaptation methods for neural-network-based signal processing, based on the differential geometry, that insist on complex-valued manifolds [14, 15, 16, 17]. This method is usally slower that FastICA, requiring more iterations to converge (about 100), but if a good initial estimate is used, as in this case with the

FastICA estimation, a few iteretions (around 20) can be used to improve the results. After this stage, the estimated sources $\hat{S}_i(\omega_k, \tau)$ are obtained.

[Figure 1 about here.]

Once the separation is obtained, the next step is to correct the permutation using the power ratio [2]. For each estimated source for a given frequency bin, its power ratio is defined as

$$\rho_i(\omega_k, \tau) = \frac{||\hat{S}_i(\omega_k, \tau)||^2}{\sum_{i=1}^{N} ||\hat{S}_i(\omega_k, \tau)||^2}. \tag{3}$$

By definition, the power ratios have values $0 \leq \rho_i(\omega_k, \tau) \leq 1$. If the i-th estimated source in bin $k-1$ correspond to the same original source that the one obtained in bin k, the correlation among $\rho_i(\omega_{k-1}, \tau)$ and $\rho_i(\omega_k, \tau)$ will be high. A coarse alignment algorithm similar to k-means clustering is applied, using the correlation as similarity measure. Next, a fine local permutation correction is applied, which compares adjacent bins and harmonic related bins. The permutation that maximizes the sum of the correlations of the given bin with the three (to each side) lateral bins, and also with the bins at double and half frequencies, is selected.

Once the permutation has been fixed, the amplitude indeterminacy shoud be corrected using the Minimum Distortion Principle [4]. Given an estimation of the separation matrix $\hat{W}(\omega_k)$, an estimation of the mixing matrix $\hat{H}(\omega_k)$ can be obtained as its inverse (or pseudoinverse if the number of mixtures and sources are not the same). The idea is to obtain the sources as measured at each sensor. Suppose that one of the estimated sources is kept, with the other ones set to zero. The application of the mixing matrix will produce a set of measurements of that individual source as seen by all the sensors. Repeating this for all the sources produces a set of so called “image sources”. In this process, the amplitude ambiguity is eliminated. Finally, the last step is a transformation to the time domain of the individual image sources, by using an ISTFT. This is the standard method against which our proposals will be compared.

2.2. Multi-bin FD-ICA

Let $X(\omega_k, \tau)$ be the vector of mixtures for the ω_k frequency associated to the k-th frequency bin, for each time τ as in (2), and let

$$\hat{X}(\omega_k) = [X(\omega_k, 1)\, X(\omega_k, 2) \cdots X(\omega_k, P)]$$

be the N-by-P single-bin data matrix for bin k, where P is the number of time frames. To produce a robust solution for the ICA subproblems, instead of using data from the present bin only (in the block labelled “Bin Data Selection” in Fig. 1), our proposal is to use data from a number L of adjacent bins to each side of the central bin, in a method we call multi-bin ICA (MB-ICA). Using the single-bin data matrix we construct the N-by-$(2L + 1)P$ multi-bin data matrix as

$$\begin{aligned} \mathcal{X}_L(\omega_k) \; = \; & \Big[\hat{X}(\omega_{k-L})\, \hat{X}(\omega_{k-L+1}) \cdots \\ & \cdots \hat{X}(\omega_k) \cdots \hat{X}(\omega_{k+L})\Big] , \end{aligned} \tag{4}$$

Let $\mathcal{X}_L(\omega_k, r)$ denote the r-th column of the multi-bin data matrix. Using this multi-bin data matrix, a separation matrix $W(\omega_k)$ for which $W(\omega_k)\mathcal{X}_L(\omega_k, r)$ result as statistical independent as possible, can be estimated by the same ICA methods described in section 2.1, and the estimated separated sources can be obtained by $Y(\omega_k, \tau) = W(\omega_k)X(\omega_k, \tau)$. After this point, the algorithm follows the same steps as the standard FD-ICA method.

Lateral bins have two effects. For one side, they produce an increase of the data used to learn the separation matrix. As all the ICA methods use some estimation of expectations, the more data available will produce better estimations of the separation matrix, which will be particularly important for short duration signals. On the other side, this produces a coupling of the separations for all bins, and thus the separation matrix will have a reduced variability among them. The reduced variability in the separation matrices would have an impact in terms of reducing the scaling and permutation problems.

There is also a theoretical justification for this multi bin usage. Under assumption of an anechoic transmission, or if the environment can be modeled by the pseudoanechoic model [8], the mixing matrix can be expressed as $H_{i,j}(\omega) = \lambda_{i,j}e^{-j\omega d_{i,j}}$, where $H_{i,j}(\omega)$ is the Fourier transform of the impulse response from source j to microphone i, $\lambda_{i,j}$ is the attenuation produced by the energy loss in the travel from the source to the microphone, which does not depends on the frequency, and $d_{i,j}$ is the delay produced during the transmission. In this way, with $d_{i,j}$ small (as it will be for small spacing between microphones as used in this work), there will be a smooth variation among mixing matrices when increasing the frequency ω. For this reason, using data from succesive frequency bins will use information from very similar mixing matrices, and the resulting mixing matrix estimation will be some kind of nonlinear average of them. This estimation will be robust, in the sense that if for some frequency bin the available data is corrupted or the signal to noise ratio is very bad, the use of information from lateral bins which do not have those problems will produce a usable estimation of the separation matrix.

[Figure 2 about here.]

The directivity patterns can be used to show the improvements produced by the use of several frequency bins. In [9] it was shown that the separation matrix produced by FD-ICA can be interpreted as a set of null beamformers, that show nulls in the direction of interfering sources. In Fig. 2a the beampattern obtained for each frequency are draw for a two mixtures-two sources case, in a room with 349 ms of reverberation time, using the standard FD-ICA method (after the solution of the scaling problem). The two sources are located at -30 and +30 degrees. In the left, the beampattern obtained from row 1 of the separation matrices is shown. As can be seen, the estimated direction shows a lot of variability with the frequency, and also there are many permutations and discontinuities that make difficult to see the right direction. In the right part of Fig. 2a, the same beampattern of the separation matrices is shown, but after solution of the permutation problem. One interesting thing to note is that there are several frequency bins where the separation method failed, which can be seen as horizontal lines with near uniform color. For those bins, there was no detection of the correct source directions. In Fig. 2b our proposed multi-bin method with $L = 2$ was applied (all the other stages of the algorithm are identical). In this case, the directivity pattern before solution of the permutation problem, in the left, shows a smoother and more consistent direction along all frequencies, and also a lower number of permutations. In the right, it can be seen that the permutations were easily solved, and the pattern shows a more consistent direction detection for all bins.

2.3. Subsampled multi-bin FD-ICA

The MB-ICA method for each bin uses $2L+1$ times the amount of data that is used in the standard method, and this will be reflected in the computation time. As a way to reduce this computational load while preserving the advantages produced by the use of lateral bins, we propose also an additional strategy: subsampling the data of the lateral bins by a factor of F. Let

$$\hat{X}_F(\omega_k) = [X(\omega_k, 0)\; X(\omega_k, F) \cdots X(\omega_k, QF)]$$

be the subsampled data matrix for bin k, where $Q = \lfloor P/F \rfloor$. We define the subsampled multi-bin data matrix as

$$\begin{aligned} \mathcal{X}_L^F(\omega_k) \quad = \quad & \Big[\hat{X}_F(\omega_{k-L})\; \hat{X}_F(\omega_{k-L+1}) \cdots \\ & \quad \cdots \hat{X}(\omega_k) \cdots \hat{X}_F(\omega_{k+L})\Big], \end{aligned} \tag{5}$$

in which it must be noted that the data for bin k has not been subsampled. Using this subsampled multibin data matrix, the separation matrix $W(\omega_k)$ can be estimated by ICA as in the previous method and the algorithm continues as already stated. The method will be called subMB-ICA in the following. This alternative will maintain the coupling among bins and thus smooth the separation process, making the permutations easier to solve when compared to the standard case. At the same time, it will reduce the computational cost of the full MB-ICA approach.

3. Results

To test the capabilities of the proposed algorithms we use artificial convolutive mixtures produced by convolving the impulse responses measured in two reverberant rooms with reverberation times (RT) of 195 ms and 349 ms, as shown in Fig. 3. We use a determined mixture of two sources and two mixtures. As the mixtures were generated artificially by convolving the source signals with measured impulse responses, we have access to the source images, which are the signals produced by each source in each microphone without the presence of the other source.

[Figure 3 about here.]

Five sentences from Albayzin database [18] were used, uttered each by two male and two female speakers, for a total of 20 utterances. The average duration of the sentences was 3.55 s. A competing speech source with the same power of the desired source was used as noise. For female speakers we used a competing male noise, and vice versa. The data were sampled at 8000 Hz. For all separation algorithms a STFT with a window length of 1024 samples, a window step size of 256 samples and windowing with a Hamming window were used. For each mixture, the separation algorithm under test was applied and the quality measures were evaluated comparing the resulting image sources with the reference ones. Individual results for each sentence were averaged to produce a single value for the room of interest.

To evaluate the quality of separation we used the signal to distortion rate (SDR), the source image to spatial distortion ratio (ISR), the signal to interference ratio (SIR) and the signal to artifact ratio (SAR) objective quality measures, as proposed in [19][1]. Also we use PESQ [20], which has been previously reported to have a high correlation with automatic speech recognition results [21]. Finally, the average processing time measured in seconds is computed, to give an idea of the computational cost of the algorithm. All the algorithms were programmed in Matlab and run in an Intel I5 processor at 2.5 GHz. [2]

The first experiment was designed to evaluate the effect of the number of bins used on the separation quality. We evaluate the use of $L = \{1, 2, 3, 4, 5\}$ lateral bins in MB-ICA. We compare these results to those of the standard FD-ICA approach. Results are shown in Table 1. Method MB-ICA with $L = 1$ lateral bin produces an improvement in PESQ, SDR, ISR and SAR with respect to the standard FD-ICA, while FD-ICA is a little better for the SIR measure. Using $L = 2$ still produces better PESQ and SAR than the standard FD-ICA, but the other quality measures are degraded. The use of more lateral bins, although produces a good convergence, may also introduce an excessive smoothing in the estimated separation matrix, which explains the degradation when increasing L. Thus, we will fix the number of $L = 1$ for the next experiments. It must be noted also that the increase in processing time is not proportional to L. This is due to a faster convergence of the ICA algorithms, which partially compensates the increased computation time due to the use of more data.

[1] We used the function bss_eval_images from the Bss_eval toolbox `http://bass-db.gforge.inria.fr/bss_eval/`

[2] A web demo and source code for our algorithms can be found in `http://fich.unl.edu.ar/sinc/web-demo/multibinica/`

[Table 1 about here.]

To evaluate the capabilities of the subsampling of lateral bins in subMB-ICA, we fixed the number of bins in $L = 1$, as suggested in the previous experiment, and changed the subsampling factor $F \in \{2, 4, 6, 8, 10\}$. We compare these results with the ones for standard FD-ICA and MB-ICA without subsampling. The results are shown in Table 2. In this case, it can be seen that the processing time decreases when subsampling factor increases, as expected, and also that for $F \in \{4, 6, 8, 10\}$ it is even smaller than that of standard FD-ICA, showing better convergence properties. For Room 1, the value of $F = 2$ gives the best results in terms of PESQ, SDR and SAR, and $F = 8$ the best results in terms of ISR and SIR. For Room 2 the results are more disperse, with $F = 6$ as the best subsampling in terms of PESQ, SDR and SIR. Following the results from Room 1, we select $F = 2$ for the last comparison, but depending on the application a higher value for F may be desirable.

[Table 2 about here.]

Finally, we compare our results with those of the standard FD-ICA method, with the ones of MB-ICA with $L = 1$ lateral bin, and the ones of subMB-ICA with $L = 1$ lateral bin and subsampling by a factor of $F = 2$. For this final test, the audio data from the Signal Separation Campaign (SiSEC 2010) for the case of "robust blind linear/nonlinear separation of short two sources two microphones recordings" was used [19]. This dataset consists on six combinations of sources in two rooms and for each room, three different source positions, for a total of 36 mixtures. The average values of the quality measures for each algorithm over all the mixture cases are shown in Table 3. The two proposed algorithms outperform the standard FD-ICA in all measures with the exception of processing time. This shows that the use of lateral bins had a positive impact in the quality of the estimation of separation matrices. Even in the subMB-ICA where not all information of lateral bins is included, there is an advantage of its usage. The best improvement is obtained by MB-ICA, at the price of about a 20% increase in computational cost. The subMB-ICA method produces results which are a compromise between the quality improvement of MB-ICA and the speed of FD-ICA, as expected.

[Table 3 about here.]

4. Conclusions

In this paper a new method to improve the quality of FD-ICA algorithms was proposed. The use of lateral bins has shown to produce a higher quality of separation, as measured by several objective quality scores. The experiments show that this improvement of quality produce a higher computational cost. To reduce it, an intermediate solution is to use a subsampling factor on the additional data. In this way the benefits of the lateral bins are mantained, but reducing the amount of extra data to be processed, thus avoiding an excessive increase of computation time. The best results were found for using one lateral bin at each side of the central bin, and using a subsampling factor of 2. Although this method was proposed and evaluated as a modification of a specific FD-ICA algorithm, this methodology can be applied in the same way to other FD-ICA algorithms that use different ICA methodologies and/or different methods for the solution of the ambiguities.

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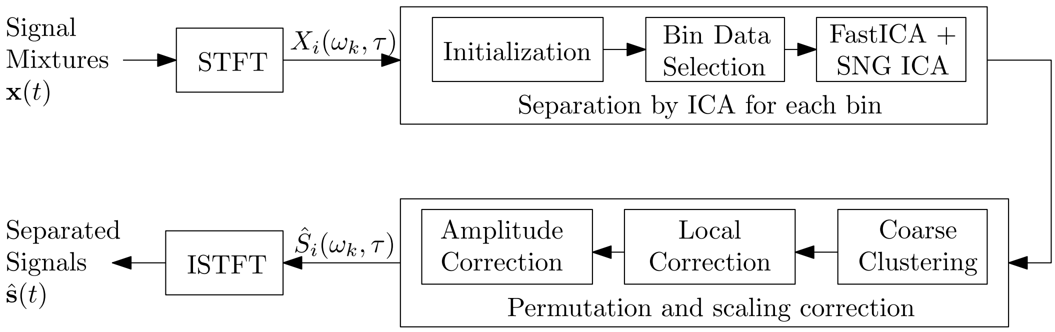
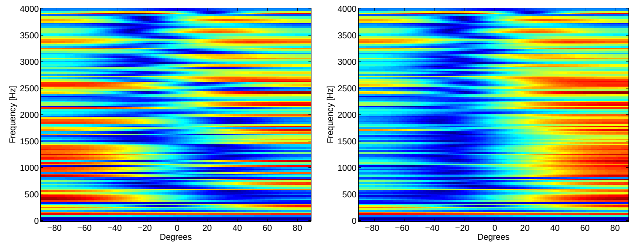
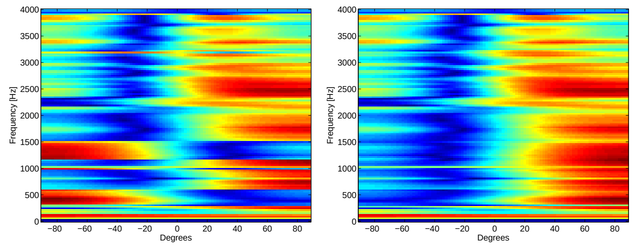


Figure 1: Flow diagram of the standard FD-ICA method

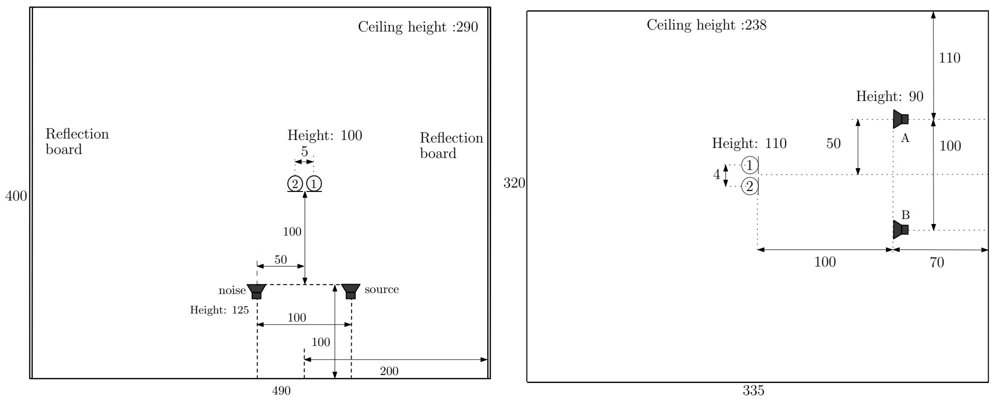


(a)



(b)

Figure 2: Beampatterns generated by the first row of separation matrices. (a) Standard FD-ICA method, before (left) and after (right) permutation correction. (b) Proposed MB-ICA, before (left) and after (right) permutation correction.



(a) (b)

Figure 3: Recording setup for the experiments. (a) Room 1: sound proof room with reflection boards, $RT = 195$ ms. (b) Room 2: real bedroom, $RT = 349$ ms. All measures are in cm.

Table 1: Comparison of standard FD-ICA against MB-ICA with different number of lateral bins. R1 is the room of Fig. 3a, R2 the room of Fig. 3b.

		FD-ICA	MB-ICA				
			L=1	L=2	L=3	L=4	L=5
R1	PESQ	2,80	**2,90**	2,81	2,76	2,71	2,69
	SDR	9,67	**10,93**	9,56	8,57	7,70	7,24
	ISR	14,98	**15,04**	13,18	12,02	11,09	10,60
	SIR	**15,53**	15,27	13,28	12,03	11,05	10,56
	SAR	12,89	16,47	16,95	**16,97**	16,56	16,38
	Time	**3,16**	4,22	4,21	4,60	4,92	5,31
R2	PESQ	2,60	**2,64**	2,57	2,52	2,52	2,50
	SDR	6,02	**6,35**	5,04	4,30	4,18	4,12
	ISR	**10,79**	10,12	8,50	7,68	7,50	7,41
	SIR	**11,09**	10,26	8,59	7,59	7,44	7,28
	SAR	9,88	**12,50**	12,36	12,29	12,49	12,88
	Time	**3,47**	3,87	4,26	4,91	5,49	6,09

Table 2: Selection of optimal subsampling factor F for the subMB-ICA method. R1 is the room of Fig. 3a, R2 the room of Fig. 3b. In boldface the best value for each measure over subMB-ICA cases.

		FD-ICA	MB-ICA			Sub MB-ICA, L=1		
			L=1	F=2	F=4	F=6	F=8	F=10
R1	PESQ	2,80	2,90	**2,88**	2,84	2,83	2,83	2,81
	SDR	9,67	10,93	**10,49**	10,10	9,85	10,16	9,98
	ISR	14,98	15,04	15,02	15,04	14,84	**15,27**	15,23
	SIR	15,53	15,27	15,37	15,49	15,40	**15,72**	15,72
	SAR	12,89	16,47	**14,97**	13,87	13,51	13,68	13,30
	Time	3,16	4,22	3,20	2,98	2,94	2,82	**2,72**
R2	PESQ	2,60	2,64	2,61	**2,62**	**2,62**	2,61	2,61
	SDR	6,02	6,35	6,18	6,25	**6,33**	6,22	6,01
	ISR	10,79	10,12	10,38	10,77	10,81	**10,87**	10,68
	SIR	11,09	10,26	10,51	10,92	**11,18**	11,13	10,83
	SAR	9,88	12,50	**11,39**	10,77	10,66	10,39	10,24
	Time	3,47	3,87	3,61	3,29	3,16	**3,14**	3,21

Table 3: Performance of the methods on SiSEC 2010 data.

	FD-ICA	MB-ICA	Sub MB-ICA
PESQ	2,69	**2,80**	2,77
SDR	2,90	**3,45**	3,41
ISR	7,70	7,95	**8,02**
SIR	8,65	**9,21**	9,13
SAR	8,69	**10,76**	10,14
Time	**3,59**	4,29	3,96